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Skin Research and Technology

Discriminative power of visual attributes in dermatology

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Background/purpose: Visual characteristics such as color and shape of skin lesions play an important role in the diagnostic process. In this contribution, we quantify the discriminative power of such attributes using an information theoretical approach.

Methods: We estimate the probability of occurrence of each attribute as a function of the skin diseases. We use the distribution of this probability across the studied diseases and its entropy to define the discriminative power of the attribute. The discriminative power has a maximum value for attributes that occur (or do not occur) for only one disease and a minimum value for those which are equally likely to be observed among all diseases.

Results: Verrucous surface, red and brown colors, and the presence of more than 10 lesions are among the most informative attributes. A ranking of attributes is also carried out and used together with a naive Bayesian classifier, yielding results that confirm the soundness of the proposed method.

Conclusion: The proposed measure is proven to be a reliable way of assessing the discriminative power of dermatological attributes, and it also helps generate a condensed dermatological lexicon. Therefore, it can be of added value to the manual or computer-aided diagnostic process.

Key words: discriminative power – information theory – entropy – skin lesion – dermatological lexicon

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DERMATOLOGY HAS widely gained from the use of technology and computers in particular. Computer-aided diagnosis is one of the ways technology assists physicians, either by storing large amounts of data or by processing characteristic diagnostic attributes. DERMIS (1) was one of the first systems developed for that purpose, and it produces a differential diagnosis graph for each case using Bayesian probability theory. The same system was later used to assess the average diagnostic accuracy of physicians (2).

Dermatologists use a variety of attributes to characterize and eventually discriminate lesions from different diseases. These attributes are mostly related to the visual characteristics of the lesions. An important question that can be posed regarding the diagnostic process is what the discriminative power of each individual attribute is. In other words, how heavily should the decision of the physician or the support system be influenced by, i.e. the red color, the round shape, or the large size of a lesion. A few studies have already been conducted in this field (3, 4), but they have either been referring to one specific disease or been solely aiming to the correct separation of similar looking diseases. Other relevant studies (5) proceed to automatically extract descriptors without any reasoning regarding their relation to the derivation of a diagnosis.

To assess which features are important in a classification task (discriminating between different categories), a ranking of the features used is necessary, and therefore, some measure regarding the discriminative power of individual features is also essential. Different metrics have been used for this purpose, such as the Fisher score (6), the Kolmogorov–Smirnov test, and the Pearson correlation (7). For features of discrete nature, mutual information (8–12), information gain (13), and the χ^2 statistic (14) have also been successfully applied.

In this article we propose an automated way to answer the question of feature discriminability for dermatological diagnosis using an information theoretical approach. We quantify the discriminative power of the visual attributes used in dermatological diagnosis in terms of entropy. Entropy (15) is a measure of

unpredictability or uncertainty regarding the value of a variable. In our case, high entropy of a given attribute essentially means that the different diseases that can give rise to the observation of that attribute (e.g. red color) are equally likely to be the cause, and therefore, this attribute has low discriminative power.

The rest of this article is organized as follows. In 'section Materials and Methods', we present in detail the materials and methods used in this contribution. In 'section Results', we present results obtained using the proposed technique. Finally, in 'section Discussion', we discuss the results and draw conclusions.

Materials and Methods

Data set

The data set for this study consists of images from 10 different skin diseases, also including different (possibly premalignant) variants of each disease. In this way, one 'disease' represents in the following a wider, more generic diagnostic group. The groups were selected based on their relatively high frequency of occurrence in general practice and the fact that they are often hard to distinguish and adequately diagnose because of their (pre) malignant nature. Furthermore, the inclusion of different variants ensures that the final results cover a broad spectrum of skin disease representations. A summary of the 10 diagnostic groups we use is presented in Table 1.

For every skin disease, 40 images have been manually selected from the digital image archive of the Department of Dermatology of the University Medical Center Groningen (UMCG). For each picture, the assigned diagnosis is verified by the medical correspondence from the Department of Dermatology, where also the results of histological and microbiological studies are taken into consideration. In cases where the clinical inspection is the only basis, a differential diagnosis is provided, and the image is assigned to the diagnosis that is considered the 'working' diagnosis. Images without correspondence are not included in this data set. To further ensure the soundness of the data, a set of selecting criteria have been used:

1. Every picture must originate from a different patient, in order for identical images not to occur in the data set (apart from cases where a patient has two different skin diseases or has a disease that looks clearly different at different parts of the body).
2. Each picture must be of good quality (sharp and properly exposed), so it can be appropriately annotated.
3. Each picture must be representative of the group it belongs to. Rare clinical variants, already treated and/or secondarily infected skin diseases are not included in the data set, as well as 'mixed pictures' (several skin diseases that overlap with each other).

During the selection process, the predilection sites on the body for some diseases have also been taken into account. For example, images of actinic keratosis and squamous cell carcinoma are included in the data set, when they occur on the head, neck, or hands and images of eczema and psoriasis are included only when skin on the torso, arms, or legs is affected. Based on the concept that the structure (and therefore the reaction pattern) of the skin is different for each body part, the above-mentioned way of selecting images ensures that a difference in appearance is a result of the skin disorder itself and not the localization of the skin defect.

TABLE 1. The skin diseases (diagnostic groups) used in this study

Disease Name
Actinic keratosis
Basal cell carcinoma
Eczema (unspecified)
Lentigo (lentigo simplex, lentigo solaris)
Melanoma (including malignant lentigo)
Mycosis (tinea corporis, tinea pedis – mocassin type, tinea versicolor)
Nevocellular naevus (including clinically atypical naevus)
Squamous cell carcinoma (including Bowen's disease)
Psoriasis (psoriasis vulgaris, psoriasis guttata)
Seborrheic verruca

Attributes used for dermatological examination

Dermatology still lacks a universal lexicon (16, , 17), and therefore, the descriptive characteristics for skin lesions can vary across studies. In this contribution, we characterize skin lesions according to the PROVOKE (18) system, which is very often used for the training of dermatologists in the Netherlands. The system is designed to systematically describe the appearance of skin lesions in a way that will help to derive

the correct diagnosis and is similar to other systems used in the literature (19–21). The definitions of the attributes we use originate from well-established sources (22–28), and they are largely based on the teaching of the French physician Darier (29).

The attributes are organized in the following 10 generic groups that we call aspects: part of the body where the lesion occurs, spatial arrangement, number of lesions observed, size of individual lesions, two- and three-dimensional shape, boundary sharpness, color, morphology, and surface of the lesions. Aspects such as 'extension' and 'skin peeling' are not included because of the quantitative and qualitative restrictions of a photographic view. Within a given aspect, there are different possible attributes: for instance, the aspect color includes the attributes (or options) normal, white, red, blue, brown, black, gray, and multicolor. An attribute that concerns a given aspect can be assigned to a case. Each such attribute is a binary feature in our terminology, assigned the value 1 when it is present and the value 0 when it is not present on a given lesion. The complete set of attributes that are associated with the different aspects is shown in Table 2.

TABLE 2.. List of aspects and attributes

Aspect	Attributes
1. Part of the body	Head, neck, trunk front, trunk back, arm, hand, buttocks, leg, foot
2. Spatial arrangement	Corymbiform, annular, linear, herpetiform, disseminated, diffuse, discrete, reticular, confluent, follicular, circinate, concentric, target shape, solitary
3. Number	One, few ($\leq$5), several ($\leq$10), many (>10)
4. Size	Extra small (1–3 mm), small (3–10 mm), medium (1–3 cm), large (3–5 cm), Extra large (>5cm)
5. 2D shape	Round, oval, polygonal, polycyclic, rectangular, linear, gyrated, dendritic, irregular, annular, arciform
6. 3D shape	Spherical, spherical with indentation, hemispheric, flat, tapered, blunt, not elevated, rough, raised edge, pendiculate
7. Boundary sharpness	Sharp, diffuse
8. Color	Normal (same color as healthy skin), white, red, blue, brown, black, gray, multicolor
9. Morphological group	Erythema, dyschromia, papular, urticarial, nodular, tumor, erythema-papulo-squamous (dermatosis), pustular (dermatosis), vesicular/bullous, ulcerative
10. Surface	Smooth, coarse, folded, wrinkled, verrucous, papillomatous, moist, purulent

Computation of the discriminative power

We quantify the discriminative power of attributes as follows. First, we consider the probability $p(f \mid \omega)$ that a certain disease ω, say psoriasis, will cause the presence of a given attribute f, for instance red color. We estimate this probability as the relative number of cases of that disease in which the concerned attribute is actually observed. For example, Fig. 1 shows the estimated probabilities of observing such lesions for the 10 skin diseases we consider. As one can read from this figure, for psoriasis the concerned probability is 0.97, while for melanoma and seborrheic verruca it is 0.

Next, we measure how uniform the distribution of probabilities of occurrence of the concerned attribute is across the studied diseases. The main idea here is that a uniform distribution (i.e. that a given attribute is equally likely to be observed in all the considered diseases) means that the concerned attribute cannot be used to discriminate between the diseases. For this purpose, we first normalize these probabilities by dividing them by their sum:

$$\hat{p}(f \mid \omega) = \frac{p(f \mid \omega)}{\sum_{\omega} p(f \mid \omega)} \tag{1}$$

We use the entropy as a measure of how uniform the considered distribution is

$$H_{\hat{p}_f} = -\sum_{\omega} \hat{p}(f \mid \omega) \log \hat{p}(f \mid \omega) \tag{2}$$

For an uniform distribution, i.e. $\hat{p}(f \mid \omega) = \frac{1}{n}$ for all n considered diseases ω, the entropy H_f reaches a maximum value of $\log n$. In contrast, for a distribution for which $\hat{p}(f \mid \omega)$ is equal to 1 for only one disease ω and equal to 0 for all other diseases, the entropy is minimal and has the value 0.

Let us consider the following quantity:

$$T_{\hat{p}_f} = 1 - \frac{H_{\hat{p}_f}}{\log n} \tag{3}$$

It takes its values in the range between 0 and 1 and is 0 if all considered diseases are equally likely to cause the observation of the attribute f. $T_{\hat{p}_f}$ takes the value 1 if the attribute f is observed for one single disease only.

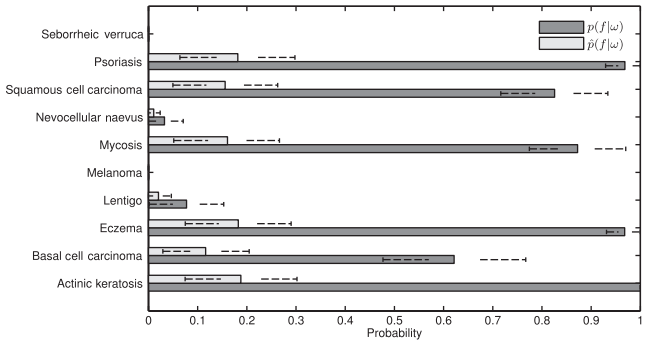

Fig. 1. Probabilities $p(f \mid \omega)$ and normalized probabilities$\hat{p}(f \mid \omega)$of observing red-colored lesions across $n = 10$ skin diseases. The whiskers represent the 95% confidence interval.

For each attribute f, we also consider the probability $p(1 - f \mid \omega) = 1 - p(f \mid \omega)$ that f is absent, given a disease ω (by definition $f = 1$ if the attribute is present and $f = 0$ if it is absent). Using Eqs. 1–3, we compute a quantity $T_{\hat{p}_{1-f}}$. Similar to $T_{\hat{p}_f}$, $T_{\hat{p}_{1-f}}$ takes its values in the range between 0 and 1, and it is 0 if all considered diseases are equally likely to induce the absence of f. $T_{\hat{p}_{1-f}}$ takes the value 1 if f is not observed for one single disease only. We consider $T_{\hat{p}_f}$ and $T_{\hat{p}_{1-f}}$ as measures of the likelihood that an attribute f or its complementary $1 - f$ is discriminative. We define the discriminative power of f as a Bayesian posterior probability

$$D_{\hat{p}_f} \propto p(f) * T_{\hat{p}_f}, \tag{4}$$

where $p(f)$ is the prior probability of occurrence of f across the diseases with which it is encountered. Similarly, using Eq. (4), we define $D_{\hat{p}_{1-f}}$ as follows:

$$D_{\hat{p}_{1-f}} \propto p(1-f) * T_{\hat{p}_{1-f}} \tag{5}$$

Finally, the discriminative power D_f for every attribute is defined as the maximum of the two quantities:

$$D_f = \max\left\{D_{\hat{p}_f}, D_{\hat{p}_{1-f}}\right\} \tag{6}$$

We estimate the value of the discriminative power D_f of a set of attributes commonly used in the diagnostics of skin diseases. We consider $n = 10$ diseases. To estimate the probabilities $p(f \mid \omega)$ that are needed to compute the value of $T_{\hat{p}_f}$, we take $N = 40$ patient cases of each disease ω and estimate $p(f \mid \omega)$ as the proportion of cases in which $f$is observed. More precisely, we also compute the 95% confidence interval for $\hat{p}(f \mid \omega)$ and use this confidence interval and the corresponding normal distribution to randomly generate 1000 values of $\hat{p}(f \mid \omega)$ from that distribution. In this way, we compute 1000 pairs of values of $T_{\hat{p}_f}$ and $T_{\hat{p}_{1-f}}$. Using Eqs. (4–6), we finally compute 1000 values of D_f and estimate their mean $\bar{D}_f$ and standard deviation σ_{D_f}.

Results

The results of our estimation of the discriminative power for the studied attributes are shown in 2–11 organized in the 10 concerned aspects. The bar graphs represent the estimated mean discriminative power $\bar{D}_f$, and the whiskers denote the 95% confidence interval for these estimations.

With respect to the place where lesions manifest themselves, the most informative attributes are the 'head' and the 'foot' (Fig. 2). Regarding 'foot' in particular, the high discriminability is due to the fact that it occurs only for lesions diagnosed as mycosis. Conversely, 'head' is present in 92.5% and 80% of the actinic keratosis and squamous cell carcinoma cases, respectively, and completely absent in cases of eczema, mycosis, and psoriasis. These results mainly reflect the criteria with which cases of the aforementioned diseases have been chosen. The feature with the lowest discriminative power is 'neck' that is encountered in very few cases of basal cell carcinoma, mycosis, naevus, and squamous cell carcinoma.

Spatial arrangement attributes with high discriminability are 'circinate', 'annular', 'solitary', and 'confluent' (Fig. 3). 'Circinate' or 'annular'

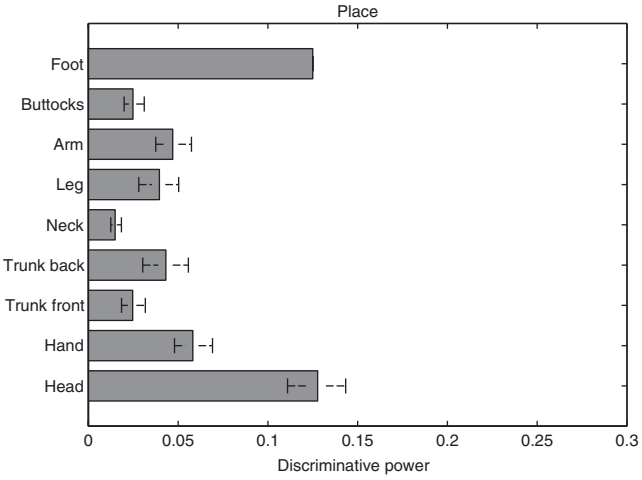

Fig. 2. Discriminative power of attributes related to the place where lesions appear.

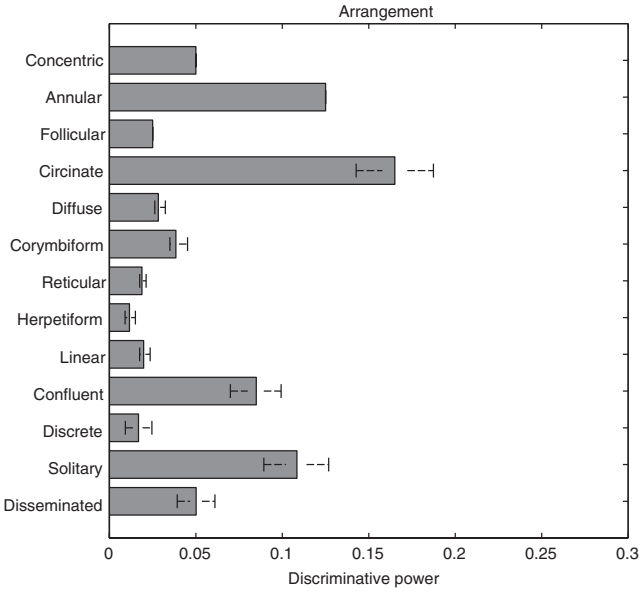

Fig. 3. Discriminative power of attributes related to the spatial arrangement of lesions.

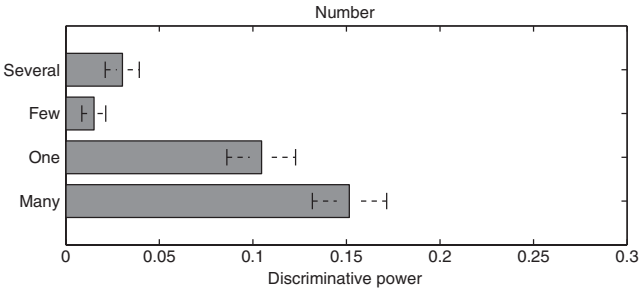

Fig. 4. Discriminative power of attributes related to the number of lesions.

arrangement is almost exclusively a characteristic of mycosis cases (a few psoriasis cases also have 'circinate' arrangement), whereas 'solitary' arrangement is mostly important when absent since that occurs often only for eczema, mycosis, and psoriasis. Lesions from these three diagnostic groups are very often 'confluently' arranged, which hardly, if at all, happens for any other of the studied diseases. 'Herpetiform' is the less discriminative among all studied arrangements. It does appear for a number of different diseases but not often enough to be of particular importance.

The two extreme attributes ('one' and 'many') regarding the number of lesions are the most discriminative (Fig. 4). Once more, eczema, mycosis, and psoriasis are those diseases where 'many' (>10) lesions appear regularly. Similarly 'one' lesion hardly appears for these three diseases, thus rendering the absence of this attribute rather important as well.

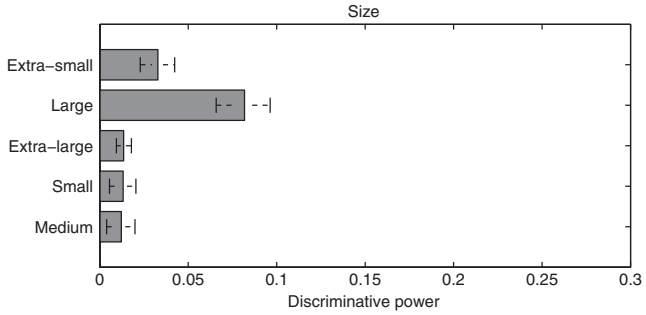

Fig. 5. Discriminative power of attributes related to the size of lesions.

With respect to size, 'large' (3–5 cm) lesions seem to be the most discriminative ones (Fig. 5). This is due to the fact that 'large' lesions appear often only for psoriasis and eczema.

Two-dimensional lesion shapes with high discriminability also mainly refer to mycosis. This is the only disease where 'arciform' shape can be encountered, and together with eczema and psoriasis, they are the only possibilities for 'annular'-shaped lesions as well (Fig. 6).

Conversely, some three-dimensional shapes can distinguish a number of diseases quite well (Fig. 7). Here, the most discriminative attribute is 'raised edge', a strong characteristic of either basal or squamous cell carcinoma. The absence of any 3D form ('not elevated') is second in ranking and is encountered in 80% of the lentigo cases and slightly less often in common skin mole (naevus) and melanoma lesions. 'Spherical' 3D shape is important regarding squamous cell carcinoma and naevus, and the absence of the attribute 'flat' also indicates a lentigo case.

Boundary sharpness is proven to be the least important of all studied aspects (Fig. 8). Both attributes in this group have very low discriminability (0.038) as they distribute quite evenly across different diseases.

'Red' is the most discriminative attribute in the aspect color. Evidently, the presence and the absence of red color are both highly informative (Fig. 9). Similarly, 'brown' color indicates cases of lentigo, nevocellular naevus, or seborrheic verruca with high probability, but it can also be indicative of actinic keratosis, eczema, mycosis, or squamous cell carcinoma when absent. 'Multi'-colored lesions are also a strong indication for mycosis although they appear in a number of other diseases as well.

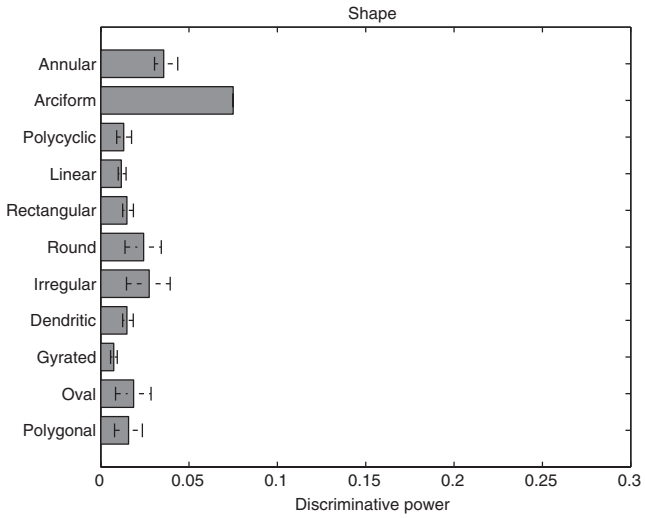

Fig. 6. Discriminative power of attributes related to the 2D shape of lesions.

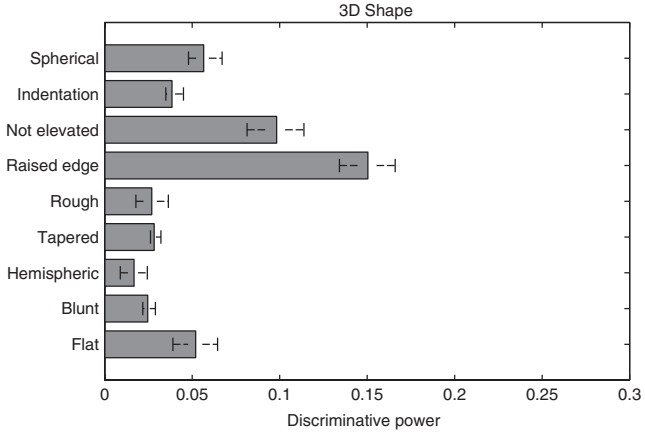

Fig. 7. Discriminative power of attributes related to the 3D shape of lesions.

Despite the fact that 'blue' color only appears in melanoma, its very low prior probability of occurrence renders it much less significant.

The morphological group is an aspect that includes a number of attributes with high discriminative power. The one ranked first among them is the 'erythema-papulo-squamous' group, highly indicative of psoriasis, mycosis, eczema, or actinic keratosis. 'Ulcerative' morphology is a clear indication of either basal or squamous cell carcinoma, and 'dyschromia' is also a very important attribute leading usually to lentigo lesions or common skin moles (and more rarely to cases of melanoma). Conversely, 'erythema' is the least important attribute in this aspect (Fig. 10).

Finally, the surface of lesions is an important aspect in the diagnostic process as well. The

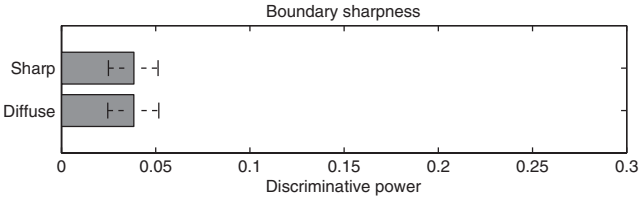

Fig. 8. Discriminative power of attributes related to the sharpness of lesion boundaries.

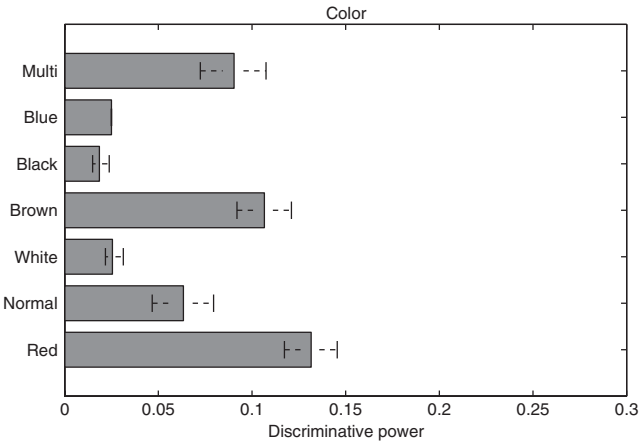

Fig. 9. Discriminative power of attributes related to the lesion color.

attribute with the highest discriminative power of all ('verrucous') belongs to this aspect and it can discriminate seborrheic verruca (Fig. 11). A 'verrucous' surface is only encountered in cases of this disease, and also 'papillomatous' surface strongly indicates the same (although it appears in cases of melanoma and naevus as well). The absence of 'coarse' surfaces is common for lentigo, naevus, and seborrheic verruca, whereas the presence of the opposite 'smooth' surface is indicative of the first two.

A note is due here to the fact that the total amount of attributes in Table 2 is 81. However, we report here on 73 of them since 8 attributes never appear in our data set and therefore the estimated discriminative power is 0. These attributes are the 'target-shaped (iris)' arrangement, the 'gray' color, the 'pendiculate' three-dimensional shape, the morphological groups 'urticarial' and 'pustular', and finally the 'wrinkled', 'folded' and 'purulent' types of surface.

Discussion

To demonstrate the reliability of the estimated discriminative power for the diagnostic attributes, we rank them based on the obtained

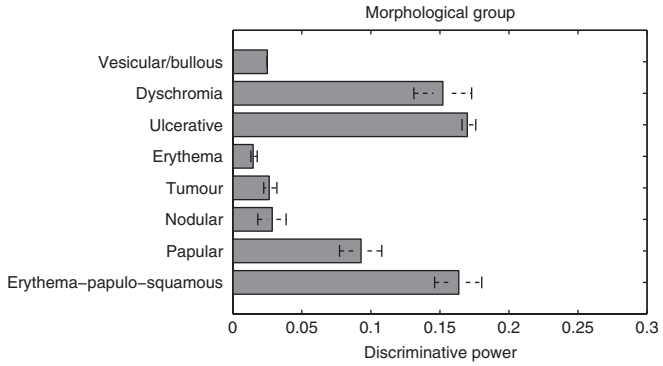

Fig. 10. Discriminative power of attributes related to the morphological group that lesions belong to.

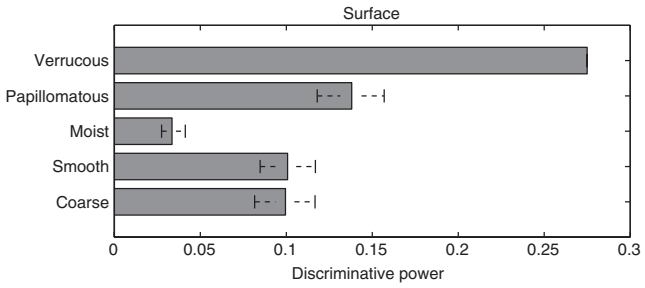

Fig. 11. Discriminative power of attributes related to the surface of lesions.

scores and use them as features in a simple classification scheme (naive Bayesian classifier). Despite the assumption that these attributes are independent from one another, the naive Bayesian classifier can be a very effective and efficient method (30). The goal is to classify the 400 images in our data set using each time one of them as a query image and the rest a database of diagnosed examples (leave-one-out cross validation). The automatic classification is considered here as a simulation of the diagnostic process, based solely on the visual characteristics of the lesions. We classify each image using initially only the attribute that reached the highest discriminability score and then we add the rest, one by one, in descending order of discriminative power. The same procedure is then repeated with the attributes sorted in ascending order of discriminative power (from the least to the most discriminative). In cases where a query image is equally likely to belong to n different diseases, with the correct one being among them, we consider $1/n$ examples to be correctly classified instead of one. The results regarding the accuracy rate are depicted in Fig. 12 as a function of the number of attributes used.

The accuracy rate is increasing proportionally to the number of attributes used. The performance of the classifier is, as expected, improving similarly to a logarithmic function when the attributes are sorted in descending order of

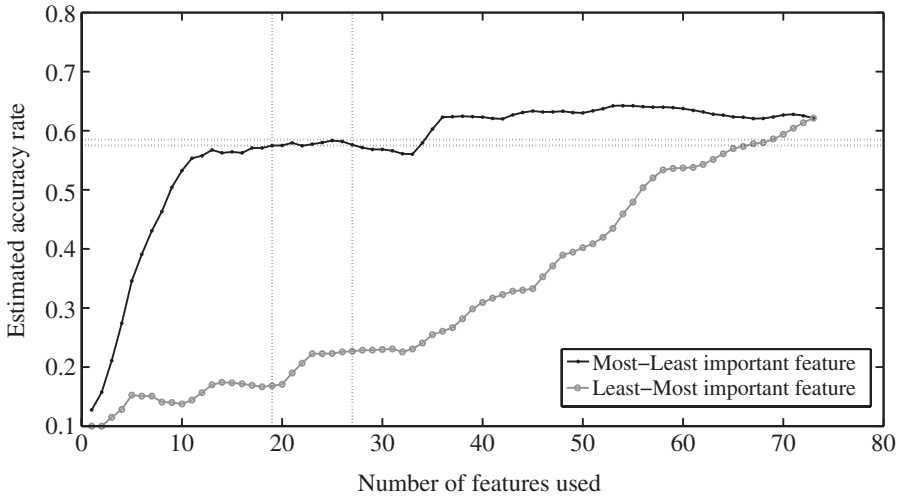

Fig. 12. Naive Bayes Classifier accuracy rate as a function of the number of attributes used.

importance. The accuracy increases very fast for the 13 most informative attributes, then the increase rate slows down considerably and finally the accuracy even decreases slightly when the least discriminative attributes are added to the system. Conversely, when the attributes are sorted in ascending order those used in the beginning have the lowest discriminability. Therefore, even when 20 attributes are used for classification, the performance hardly exceeds the level of random chance (accuracy $\approx \frac{1}{10}$).

A note is due here to the soundness of the dermatological lexicon (aspects and attributes) used in this study to characterize lesions. Using the annotations based on this lexicon, the naive Bayesian classifier reaches an accuracy of 64.6%. This accuracy rate is comparable to the ability of a trained physician to determine the correct diagnosis by just viewing the images of lesions. Relevant studies (31–32) report results that place the reliability of dermatologists' 'digital image consultations' in the same order of magnitude ($\sim$60%). The similar accuracy rates strongly suggest that the set of attributes we use does not disregard important characteristics, and it describes the lesions well enough for the accurate derivation of a diagnosis.

Finally, in Fig. 12, we observe that when using a number between 19 and 27 the most important attributes (the region marked by the vertical grid lines), the classification accuracy essentially reaches for the first time a 'plateau' (marked by the horizontal grid lines), ranging between 57.5% and 58.5%. To achieve this result, attributes from all aspects apart from the boundary sharpness are included. In addition, when using up to 22 attributes, 2D shape is completely absent as well and otherwise only 'arciform' shape does appear. Therefore, the aspects of boundary sharpness and 2D shape can be considered of lesser significance as a whole and hence left out of the dermatological lexicon (PROVOKE) without substantial loss in the accuracy of the diagnosis.

Summary and Conclusions

In this article we propose a method to quantify the discriminative power of attributes used by physicians in the dermatological diagnostic process using the entropy of the corresponding distributions of probabilities of occurrence. The empirical results indicate as the most discriminative attributes the 'verrucous' and 'papillomatous' surfaces, the 'ulcerative', 'dyschromia' and 'erythema-papulo-squamous' morphological groups, the presence of more than 10 lesions ('many'), the 'circinate' arrangement, the 'raised edge' 3D shape, and the 'red' color. On the other hand, attributes such as the 'round' and 'oval' 2D shapes, the 'discrete' arrangement, or the 'small' size are not of particular importance for the objective of distinguishing between different diseases. We additionally demonstrate that this measure is a reliable way of assessing the discriminability of different attributes.

With regard to the set of aspects and attributes we use, there is evidence suggesting that it provides an adequate description for skin lesions. Furthermore, using the discriminative power scores of the individual attributes, we are able to detect the minimal influence of the aspects boundary sharpness and 2D shape. Hence, we introduce a condensed version of the PROVOKE dermatological lexicon that still yields good results using only 8 aspects and 22 attributes. The new lexicon comprises the

TABLE 3. Condensed dermatological lexicon

Aspect	Attributes
1. Part of the body	**Head**, neck, trunk front, trunk back, arm, hand, buttocks, leg, **foot**
2. Spatial arrangement	Corymbiform, **annular**, linear, herpetiform, disseminated, diffuse, discrete, reticular, **confluent**, follicular, **circinate**, **concentric**, target shape, **solitary**
3. Number	One, few ($\leq$5), several ($\leq$10), many (>10)
4. Size	Extra small (1–3 mm), small (3–10 mm), medium (1–3 cm), **large (3–5 cm)**, extra large (>5 cm)
5. 2D shape	Round, oval, polygonal, polycyclic, rectangular, linear, gyrated, dendritic, irregular, annular, arciform
6. 3D shape	Spherical, spherical with indentation, hemispheric, flat, tapered, blunt, **not elevated**, rough, **raised edge**, pendiculate
7. Boundary sharpness	Sharp, diffuse
8. Color	Normal (same color as healthy skin), white, **red**, blue, **brown**, black, gray, **multicolor**
9. Morphological group	Erythema, **dyschromia**, **papular**, urticarial, nodular, tumor, **erythema-papulo-squamous (dermatosis)**, pustular (dermatosis), vesicular/bullous, **ulcerative**
10. Surface	**Smooth**, **coarse**, folded, wrinkled, **verrucous**, **papillomatous**, moist, purulent

aspects and attributes in bold as shown in Table 3.

Finally, it is worth noting that the proposed discriminability measure can be part of any system that stores patient cases in a dermatology department of a medical institution, regardless of the precise nature of the attributes that the institution uses to describe lesions. Given a well-defined dermatological lexicon, a continuously expanding knowledge base can be created as new cases are examined and diagnosed. The results that the proposed measure will then produce can be beneficial in the daily diagnostic procedure, but they could also serve as a feature weighting mechanism for computer-aided dermatological diagnosis systems.

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